

Bayesian Approach in the Modal Analysis of Electromechanical Oscillations

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Abstract—This paper presents a Bayesian approach for identifying the modal parameters (i.e., frequency, damping ratio, and modal excitation) of electromechanical modes. The proposed approach identifies the modal parameters and calculates their uncertainty using ambient phasor measurement unit (PMU) measurements from a power system. The method is applied in the frequency domain on a selected frequency band, which significantly simplifies the identification. The performance of the method is studied with simulated data from the IEEE New England test system and the Nordic power system simulation model. In addition, measured PMU data from the Nordic power system are used. The results indicate that the modal parameters of electromechanical modes can be identified reliably and their identification uncertainty can be fundamentally calculated using the proposed method. Thus, the Bayesian approach is a promising identification method for wide-area monitoring of electromechanical oscillations.

Index Terms— Bayes' theorem, electromechanical oscillation, modal analysis, PMU measurements, power system dynamics.

I. NOMENCLATURE

\mathbf{i} Purely imaginary number, $\mathbf{i}^2 = -1$
 \mathbf{I}_n Identity matrix of dimension n
 n Number of measured degrees of freedom (DOFs)
 m Number of modes within selected frequency band
 N Number of measured time instants
 N_q Fast Fourier transform (FFT) frequency index at Nyquist frequency
 N_f Number of FFT frequencies in the selected frequency band
 Θ Set of modal parameters to be identified
 f_i Natural frequency (Hz) of the i -th mode
 ω_i Natural frequency (rad/sec) of the i -th mode

ζ_i Damping ratio of the i -th mode
 Φ_i Partial mode shape of the i -th mode of the measured DOFs
 Φ Partial mode shape matrix of the measured DOFs
 S_e Power spectral density (PSD) of prediction error
 S_{ij} Cross PSD between modal excitations of the i -th and j -th mode
 \mathbf{S} PSD matrix of modal excitations
 $p_i(t)$ Modal excitation of the i -th mode at time t
 D Measured data
 \mathbf{M} Matrix containing the inertia coefficients
 \mathbf{C} Matrix containing the damping coefficients
 \mathbf{K} Matrix containing the synchronizing power coefficients
 $\mathbf{F}(t)$ Vector of natural excitation to system at time t
 $\mathbf{x}(t)$ Vector of rotor angles of system at time t
 Ψ_i Mode shape vector of the i -th mode with all DOFs
 $\eta_i(t)$ Modal response of the i -th mode
 \mathbf{y}_j Vector of measured data at time instant j
 Δt Sampling time interval (sec)
 f_k FFT frequency (Hz)
 \hat{F}_k Scaled FFT of measured data at FFT frequency f_k
 η_{ik} Scaled FFT of $\eta_i(t)$ at FFT frequency f_k
 p_{ik} Scaled FFT of modal excitation at FFT frequency f_k
 ϵ_k Scaled FFT of prediction error at FFT frequency f_k
 L Negative log-likelihood function
 h_{ik} Transfer function of the i -th mode at FFT frequency f_k
 \mathbf{H}_k Transfer matrix at FFT frequency f_k

II. INTRODUCTION

The electromechanical oscillations of synchronous generators are characteristic of electrical transmission systems. In some transmission systems, the damping of the oscillations is the limiting factor for the transmission capacity, and thus, the thermal capacity of the lines cannot be fully utilized. Moreover, in the most severe situations, unstable oscillations may lead to system collapse. Thus, analyzing (off-line) and monitoring (in real-time) the oscillatory stability of power systems is essential.

Often, the oscillatory stability of power systems can be

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monitored by identifying the modal characteristics of the existing electromechanical oscillatory modes. The modal characteristics can be identified for example using the measurements from phasor measurement units (PMU). Furthermore, wide area monitoring systems (WAMS) including several PMUs have enabled the use of multiple synchronized measurement signals received from several locations in the power system to be used for the monitoring of the modes.

Typically, the oscillatory modes can be monitored in real-time by using identification methods and PMU measurements from ambient power system conditions. In the past, several methods have been proposed for identifying the modes from ambient measurements [6]–[17].

This paper proposes a Bayesian approach for identifying the modal properties of power systems from ambient measurements. The proposed approach has been found to be highly effective in identifying the oscillatory dynamics of civil and mechanical structures with quantifiable identification precision [2]–[5]. It has never been used for identifying electromechanical modes and there is much room for adapting this approach for improving security and utilization of power systems.

In this paper, the performance of the proposed approach is validated using simulated data as well as real PMU measurement data. The paper shows that the Bayesian approach is a well suited and reliable method for monitoring of electromechanical modes.

There are several benefits in using the proposed Bayesian approach. Firstly, unlike several previously published methods, e.g. [12] and [14]–[16], the proposed Bayesian approach does not use statistical proxies (e.g., correlation function, sample power spectral densities) calculated from the measurement data for modal identification. Rather, the identification information about the parameters is fundamentally expressed using Bayes Theorem in terms of a probability distribution conditional on the data and modeling assumptions.

Secondly, the proposed method identifies the modes based on the fast Fourier transform (FFT) information on a selected frequency band. Compared with time-domain methods, such as [6]–[11], [13]–[16], this significantly simplifies the identification model and reduces modeling error in other unmodeled frequency bands, and therefore, improves the robustness of the method. To illustrate this, Fig. 1 shows the power spectrum of an example PMU measurement collected from the Nordic Power system, where the mode of interest is around 1 Hz. However, there are activities of different nature over the whole sampling band up to Nyquist frequency (25 Hz in this case). The ambient excitation source and measurement noise differ in order of magnitude and characteristics over different frequency regimes. Using a time domain approach, it is difficult to have a simple model that accounts for the various frequency characteristics. However, using a frequency domain approach, only the FFTs within the indicated band in Fig. 1 are used for making inference. The frequency characteristics that are irrelevant or difficult to model are

ignored by simply excluding the FFTs in their band. In addition, this does not require any band-pass filtering. In this sense, the frequency domain provides a natural partition of information particularly suitable for ambient data. Since the raw FFT is used and no averaging is involved, distortion effects due to leakage or smearing is significantly reduced compared with conventional methods involving sample spectral estimates [22].

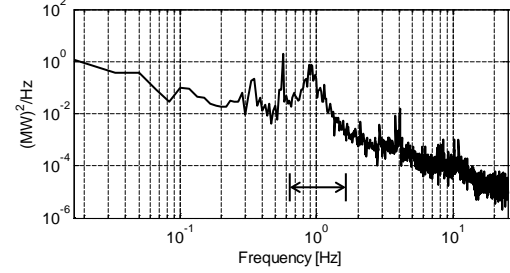


Fig. 1. Power spectrum of an example data set collected from the Nordic power system.

Thirdly, for close modes the identified mode shape vectors of the Bayesian method are the real ones and they need not be orthogonal. This is in contrast with existing methods, which can only yield the “operational deflection shape” (from eigenvector decomposition) that are necessarily orthogonal.

Fourthly, the Bayesian method also allows the uncertainty of modal parameters (i.e., frequency, damping ratio, modal excitation) to be calculated. This is fundamentally in terms of a posterior distribution that is a function of measured data rather than confidence intervals (in non-Bayesian methods) that are only estimates of “inherent uncertainty” associated with conceptually repeated experiments under small perturbations. Closed-form asymptotic expressions are also presented for the leading order term of the identification uncertainty to provide insights on the achievable precision of modal parameters. The uncertainty information provides a basis for power system operators and analysts to design appropriate configurations for reliable identification and proper interpretation of the modal identification results. Further discussion regarding the uncertainty of modal parameters can be found in [21].

The paper is structured as follows. Section III describes the theoretical background of the Bayesian approach. Section IV presents the simulated data and the PMU measurements used for the performance analysis of the proposed approach. The analysis results using both simulated and measured data are presented in Section V. Section VI discusses the applicability of the proposed approach for the analysis of electromechanical oscillations. The conclusions of this paper are given in Section VII.

III. METHODOLOGY

A. Bayesian Approach

Let θ denote the set of parameters to be identified from a set of measured data D . A Bayesian approach to system identification recognizes the fact that it is philosophically impossible to identify exactly the value of θ because of

limited amount of available data, measurement noise, modeling error, etc. Instead, all information that can be extracted from D on θ is encapsulated in the ‘posterior’ (i.e., given data) probability density function (PDF) $p(\theta|D)$. Using Bayes’ Theorem, the posterior PDF is given by

$$p(\theta|D) = p(D|\theta)p(\theta)/p(D) \quad (1)$$

Strictly speaking, all the terms in (1) are conditional on modeling assumptions but the latter have been omitted to simplify notations. In (1), for a given model assumed in identification, $p(D)$ is a constant and so it does not affect the shape of the PDF; $p(\theta)$ is often called the ‘prior PDF’ (i.e., before data is incorporated) and $p(D|\theta)$ the ‘likelihood function’, which gives the PDF of the data for a given θ and must be derived based on modeling assumptions that relate θ to D . The spread of $p(\theta)$ reflects one’s knowledge on parameters in the absence of data while the spread of $p(D|\theta)$ reflects how sensitive the likelihood of data is to parameters. Sensitivity in $p(D|\theta)$, which is a joint distribution of data, increases with sample size and so for sufficiently large sample size (which is the case in modal identification) the variation of $p(D|\theta)$ dominates that of $p(\theta)$. Thus, practically one can take

$$p(\theta|D) \propto p(D|\theta) \quad (2)$$

B. Ambient Modal Identification

It is shown in [14] that in small signal analysis (i.e. in the vicinity of the current operating point) the oscillatory behavior of each generator in the power system can be described by:

$$\mathbf{M}\ddot{\mathbf{x}}(t) + \mathbf{C}\dot{\mathbf{x}}(t) + \mathbf{K}\mathbf{x}(t) = \mathbf{F}(t) \quad (3)$$

where \mathbf{M} , \mathbf{C} and \mathbf{K} are diagonalizable matrices containing the inertia coefficients, damping coefficients and synchronizing power coefficients of each generator, respectively. Here, $\mathbf{x}(t)$ is a vector containing the rotor angle deviations of the generators around their equilibrium points and \mathbf{F} is the vector of the natural excitation of the system. The main causes of the excitation are the loads, which are randomly varying by nature. In addition, minor transients such as minor switching events, or minor faults can be considered as the natural excitation of the system [15].

As \mathbf{M} , \mathbf{C} and \mathbf{K} are diagonalizable, the solution of $\mathbf{x}(t)$ can be expressed as a sum of modal contributions:

$$\mathbf{x}(t) = \sum_i \boldsymbol{\psi}_i \eta_i(t) \quad (4)$$

where $\boldsymbol{\psi}_i$ ($i=1,2,\dots$) are the mode shape vectors of the system satisfying the generalized eigenvalue problem

$$\mathbf{K}\boldsymbol{\psi}_i = \omega_i^2 \mathbf{M}\boldsymbol{\psi}_i \quad (5)$$

In (4), η_i is the scalar modal response satisfying the uncoupled equation of motion:

$$\ddot{\eta}_i(t) + 2\zeta_i \omega_i \dot{\eta}_i(t) + \omega_i^2 \eta_i(t) = p_i(t) \quad (6)$$

where $\omega_i = 2\pi f_i$; f_i and ζ_i are respectively the natural frequency (Hz) and damping ratio of the mode; and

$$p_i(t) = \frac{\boldsymbol{\psi}_i^T \mathbf{F}(t)}{\boldsymbol{\psi}_i^T \mathbf{M} \boldsymbol{\psi}_i} \quad (7)$$

is the modal excitation.

Let $\{\hat{\mathbf{y}}_i \in R^n\}_{i=0}^{N-1}$, be a set of discrete time history at n measured degrees of freedom (DOFs) of the system under ambient condition. Given the data, the goal is to identify the system modal properties, which primarily consist of the natural frequencies, damping ratios and mode shapes. In the context of the Bayesian approach, it is required to formulate the likelihood function $p(D|\theta)$.

Processing the ambient (unfiltered) measurements directly would require a model that explains all the modes in the sampling bandwidth (from zero to the Nyquist frequency). The measurements can also contain frequency components from unknown system dynamics, which the theoretical model cannot explain. In view of these, it is preferable to operate in the frequency domain and use the FFT of time history on a selected frequency band around the modes of interest as data D for Bayesian inference. This significantly reduces the complexity of the model as it only needs to account for the dynamics of the modes in the selected frequency band.

Define the scaled FFT of $\{\hat{\mathbf{y}}_i \in R^n\}_{i=0}^{N-1}$ by

$$\hat{\mathcal{F}}_k = \sqrt{\frac{\Delta t}{N}} \sum_{j=0}^{N-1} \hat{\mathbf{y}}_j e^{-2\pi i j k / N} \quad k = 0, \dots, N-1 \quad (8)$$

where Δt is the sampling interval in seconds and $i^2 = -1$. For $k \leq N_q$, where N_q (index at Nyquist frequency) is the integer part of $N/2$, $\hat{\mathcal{F}}_k$ corresponds to frequency $f_k = k / N\Delta t$. The FFT in (8) is scaled by the factor $\sqrt{\Delta t / N}$ so that $E[\hat{\mathcal{F}}_k \hat{\mathcal{F}}_k^*]$ is equal to the power spectral density (PSD) matrix of the data process.

Let $D = \{\hat{\mathcal{F}}_k\}$ denote the collection of FFTs within the selected frequency band for the modal identification. To formulate the likelihood function $p(D|\theta)$, it is necessary to derive the joint distribution of $\hat{\mathcal{F}}_k$ for a given set of modal parameters θ . Not only does θ need to contain the parameters of interest (e.g., natural frequency and damping of

the electromechanical modes) but also those that together can allow $p(D|\boldsymbol{\theta})$ to be derived explicitly. Within the selected frequency band $\hat{\mathcal{F}}_k$ is modeled as

$$\hat{\mathcal{F}}_k = \sum_i \boldsymbol{\Phi}_i \eta_{ik} + \varepsilon_k \quad (9)$$

where the sum is over the modes in the selected frequency band only; η_{ik} denotes the scaled FFT of $\eta_i(t)$; and ε_k is the scaled FFT of the ‘prediction error’ (e.g., measurement noise). It is assumed that the prediction errors at different channels are independent and identically distributed (i.i.d.) with a constant PSD of S_e within the selected frequency band. Taking the scaled FFT on (6) gives

$$\eta_{ik} = h_{ik} p_{ik} \quad (10)$$

where

$$h_{ik} = (2\pi f_k)^{-2} [(\beta_{ik}^2 - 1) + \mathbf{i}(2\zeta_i \beta_{ik})]^{-1} \quad (11)$$

is the transfer function and $\beta_{ik} = f_i / f_k$ is the ratio of the natural frequency f_i to the FFT frequency f_k . In (10), p_{ik} is the scaled FFT of the modal excitation $p_i(t)$, which is assumed to have a constant PSD matrix of \mathbf{S} in the selected frequency band. The above context is sufficient for deriving the joint PDF of $\{\hat{\mathcal{F}}_k\}$, where $\boldsymbol{\theta}$ consists of, for the modes in the selected frequency band, the natural frequencies $\{f_i\}$, damping ratios $\{\zeta_i\}$, the mode shapes (confined to the measured DOFs) $\boldsymbol{\Phi}$, the parameters characterizing the modal excitation PSD matrix \mathbf{S} and the prediction error PSD S_e .

The likelihood function $p(D|\boldsymbol{\theta}) = p(\{\hat{\mathcal{F}}_k\}|\boldsymbol{\theta})$ can be derived using asymptotic results of FFTs of stationary processes for long data lengths [1]. Essentially, it can be shown that $\{\hat{\mathcal{F}}_k\}$ at different frequencies (k ’s) are asymptotically independent. Also, $\text{Re}\hat{\mathcal{F}}_k$ and $\text{Im}\hat{\mathcal{F}}_k$ are jointly Gaussian and their covariance matrix can be expressed in terms of $\boldsymbol{\theta}$. Consequently, it can be shown that [2]

$$p(D|\boldsymbol{\theta}) = e^{-L(\boldsymbol{\theta})} \quad (12)$$

where

$$L(\boldsymbol{\theta}) = nN_f \ln \pi + \sum_k \ln \det \mathbf{E}_k(\boldsymbol{\theta}) + \sum_k \hat{\mathcal{F}}_k^* \mathbf{E}_k(\boldsymbol{\theta})^{-1} \hat{\mathcal{F}}_k \quad (13)$$

is the “negative log-likelihood function” (NLLF);

$$\mathbf{E}_k(\boldsymbol{\theta}) = \boldsymbol{\Phi} \mathbf{H}_k \boldsymbol{\Phi}^T + S_e \mathbf{I}_n \quad (14)$$

is the theoretical PSD matrix of the measured data;

$$\boldsymbol{\Phi} = [\boldsymbol{\Phi}_1, \dots, \boldsymbol{\Phi}_m] \in \mathbb{R}^{n \times m} \quad (15)$$

is the mode shape matrix; \mathbf{I}_n denotes the identity matrix of dimension n ; $\mathbf{H}_k \in \mathbb{C}^{m \times m}$ is a transfer matrix whose (i, j) -entry is given by

$$\mathbf{H}_k(i, j) = S_{ij} h_{ik} h_{jk}^* \quad (16)$$

and S_{ij} is the (i, j) -entry of the modal excitation PSD matrix \mathbf{S} .

C. Computation of Posterior Statistics

The statistical properties of $\boldsymbol{\theta}$ can be extracted from the posterior PDF or equivalently the NLLF in (13), which is essentially a computational problem. For modal identification problems with sufficient data, the posterior PDF has a single peak, say $\hat{\boldsymbol{\theta}}$. This is the ‘most probable value’ (MPV) as it has the highest probability density according to the posterior PDF. Using a second order Taylor expansion of the NLLF around $\hat{\boldsymbol{\theta}}$, the posterior PDF can be approximated by a Gaussian PDF centered at the MPV. It can be shown that the covariance matrix is then given by the inverse of the Hessian of the NLLF [2].

Computing the MPV by brute-force optimization with the NLLF is not feasible because in practical problems the number of parameters is large. Efficient algorithms have been developed in various cases, including, e.g., well-separated modes [2] and close modes [3]. Essentially, it is found that the MPV of the mode shape vector can be found almost analytically, in such a way that the full set of modal parameters can be found iteratively by optimizing each individual group in turn until convergence. A recent review with applications in civil engineering can be found in [4]. Analytical expressions for the Hessian of the NLLF have also been derived so that the covariance matrix of the modal parameters can be calculated efficiently and accurately without resorting to a finite difference method.

D. Uncertainty laws

In addition to modal identification algorithm, closed form expressions have also been derived for the identification uncertainty of the modal parameters under asymptotic situations of long data and low damping [5]. They are collectively known as ‘uncertainty laws’. In particular, assuming that the selected bandwidth is $f(1 \pm \kappa \zeta)$ where f is the natural frequency (in Hz), ζ is the damping ratio and κ is a dimensionless bandwidth factor characterizing the usable bandwidth, it can be shown [5] that the posterior coefficient of variation (c.o.v. = standard deviation/mean) of the damping ratio is asymptotically given by

$$\delta \sim [2\pi \zeta B(\kappa) N_c]^{-1/2} \quad (17)$$

where N_c is the data duration expressed as a multiple of the

natural period; and

$$B(\kappa) = \frac{2}{\pi} \left[\tan^{-1} \kappa + \frac{\kappa}{\kappa^2 + 1} - \frac{2(\tan^{-1} \kappa)^2}{\kappa} \right] \quad (18)$$

is the ‘data length factor’ being a monotonic increasing function of κ reflecting the effect of widening the usable band on identification precision. This equation can be used for assessing and planning the measurement configuration required to achieve a specified identification accuracy in the modal parameters. For example, assuming 1 % damping, it requires about 300 natural periods to achieve a c.o.v. of 30 % in the damping ratio. Uncertainty laws for other modal parameters are also available [5].

IV. SIMULATED AND MEASURED TEST DATA

A. Simulated Data from a Test System with Known Damping

The 39-bus New England test system [18] consists of 10 generators and 19 loads. Fig. 2 presents a single line diagram of the test system.

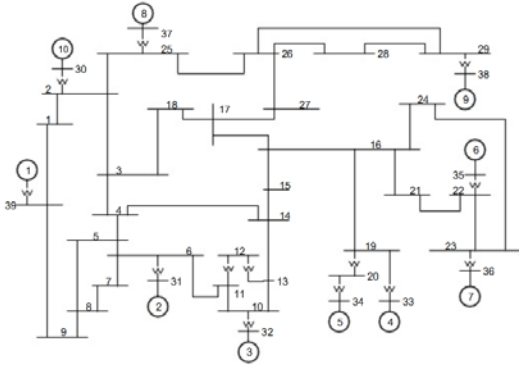


Fig. 2. Single line diagram of the New England test system [18].

The test system was linearized using the Linear System Analysis (LSYSAN) program of the Power System Simulator for Engineering (PSS/E) software [19]. According to the linear analysis, the dominant mode with the lowest damping in the studied power flow case is a 0.62 Hz mode with a damping ratio $\zeta = 6.4\%$. Note that these values can be considered as the reference values for the analysis, but they should not be considered as the exact "true" values for frequency and damping. This mode will be the focus of further analysis in this study.

Synthetic measurement data representing the system behavior under ambient conditions were generated with the non-linear test system model. The data are used for the performance analysis of the Bayesian method. The data were obtained by perturbing each load in the test system with additive white noise with a small variance. The simulations were performed with the PSS/E-software [19]. The obtained data set consists of 15 minutes of active power flow data from 3 selected lines (Bus 1 – Bus 2, Bus 1 – Bus 39 and Bus 9 – Bus 39), where the 0.62 Hz mode is clearly observable. The data were sampled with 10 Hz sampling frequency.

B. Simulated Data from the Detailed Model of the Nordic Power System

The Nordic power system (Fig. 3) is a synchronous system consisting of the grids of Finland, Sweden, Norway, and Eastern Denmark. In this study, a detailed simulation model [13] of the Nordic power system is used. The model has approximately 6000 buses, 1700 machines and 2600 loads.

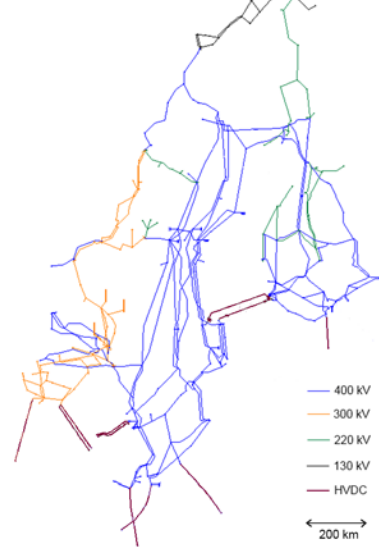


Fig. 3. A diagram of the main transmission lines of the Nordic power system.

The power flow case in the simulation was tuned in such a way that damping of the dominant 0.3 Hz inter-area mode is approximately 7 %. These values were obtained by simulating a small transient and performing Prony analysis for the transient. Note that these values can be considered as the reference values for the analysis, but they should not be considered as the exact "true" values for frequency and damping. In this mode, the generators at Southern Finland oscillate against the generators at Southern Sweden and Norway. To reflect the actual system behavior under ambient conditions, randomly varying loads were used to excite the oscillations. The load variation results in the driving noise being close to Gaussian. Furthermore, the simulated oscillation amplitudes were close to actual measured oscillation amplitudes in the grid. The recorded quantities were voltage angle differences from three generator buses situated in Finland (the reference bus is in Denmark).

In practical situations, a certain measurement noise is present in the PMU measurements. To analyze the performance of the Bayesian method with respect to measurement noise, different amounts of Gaussian white noise were added to the simulated signals and data sets with different signal-to-noise ratios (SNR) were obtained. The SNRs were calculated by (linear scale):

$$\text{SNR} = \left(\frac{\sigma_{\text{signal}}}{\sigma_{\text{noise}}} \right)^2 \quad (19)$$

where σ_{signal} and σ_{noise} are the signal and noise standard

deviation, respectively.

C. Measured Data from the Nordic Power System

In addition to the simulated data, real measured PMU data are used in this paper to test the performance of the Bayesian method. The data were recorded using two PMUs installed in the transmission system of Northern Finland. Fig. 4 shows the grid map of the area and the measurement locations.

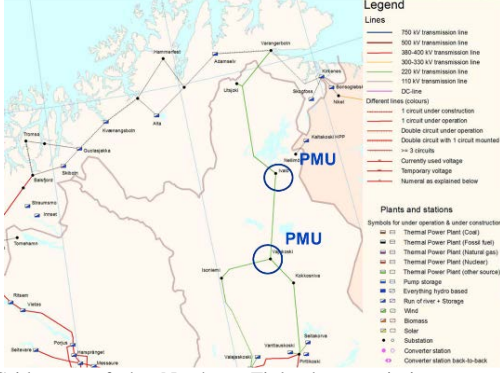


Fig. 4. Grid map of the Northern Finland transmission system and the measurement locations [20].

The Northern Finland transmission system is characterized by long transmission distances, large amounts of hydro power production, and small consumption. When power transmission is from North to South, the power transfer capacity of the grid is limited by the damping of electromechanical oscillations.

Often, the dominant electromechanical mode in the area is observed around the frequency of 0.8 Hz. When exposed to this mode, the generators in Northern Finland and Northern Norway oscillate against the rest of the Nordic system. This mode is further analyzed in Section V C.

The collected measurement data contain 24 hours of active power flow from two 220 kV transmission lines. Fig. 5 presents a sample excerpt of a measurement.

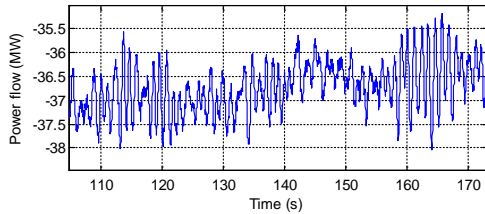


Fig. 5. Sample excerpt of a PMU measurement from Northern Finland (active power flow from a 220 kV line).

There are some small transients in the collected measurement data set. These transients were caused by minor changes (i.e., small switching events) in the grid. One of the transients is shown in Fig. 6. To obtain reference values for the frequency and damping ratio of the dominant mode, two transients (one in the beginning of the data set and one in the end part of the data set) were analyzed using Prony analysis. The results of the Prony analysis were as follows:

- Transient at 34 min (near the beginning of data set):
 $f \approx 0.93 \text{ Hz}$, $\zeta \approx 5 \%$
- Transient at 20 h 7 min (near the end of data set):
 $f \approx 0.88 \text{ Hz}$, $\zeta \approx 5 \%$

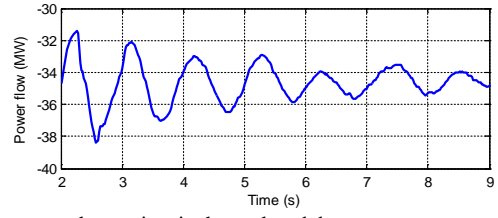


Fig. 6. An example transient in the analyzed data set.

V. RESULTS

A. Modal Identification Results for the Simple Test System

Fig. 7 shows an example power spectrum for the New England test system. The spectrum is calculated using a 1000 s extract of the ambient data as described in Section IV A. The figure also shows the selected frequency band whose FFT will be used for modal identification using the Bayesian method.

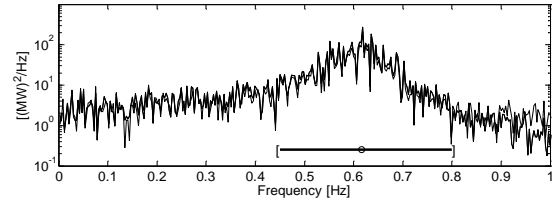


Fig. 7. Power spectrum (smoothed for visualization) of the data from the New England test system. Horizontal bar indicates selected frequency band for modal identification.

Using the FFT data in the selected frequency band (Fig. 7), the most probable values (MPV) and posterior variances of the modal parameters were calculated using the proposed Bayesian algorithm. Fig. 8 shows the results with different analysis window lengths, from 60 seconds to 900 seconds.

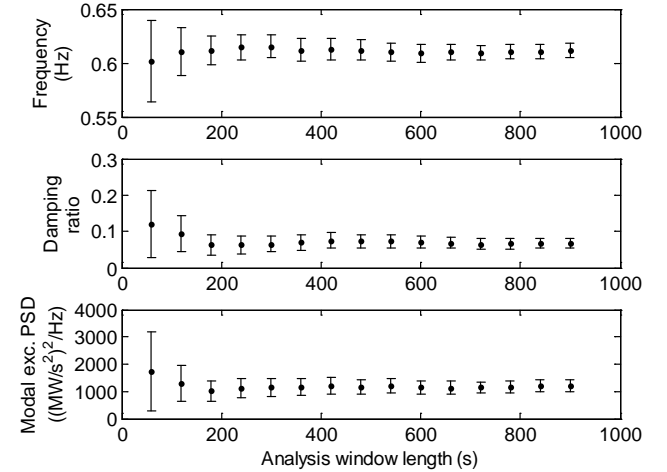


Fig. 8 Modal identification results for the New England data for different analysis window lengths. Frequency in Hz and modal excitation PSD in $(\text{MW/s}^2)/\text{Hz}$. Dot: MPV; error bar: \pm two standard deviations. The reference values (based on linear analysis, Section IV A) for frequency and damping ratio of the studied mode are 0.62 Hz and 0.064, respectively.

The results in Fig. 8 indicate that the proposed Bayesian method is functional. As the analysis window length increases, the posterior PDF of each modal parameter, as depicted by the MPV (dot) and the two-standard deviation error bar, is focused towards the reference values (Section IV A) that

corresponds to the data. That is, the more information is incorporated for identification, the higher the identification precision.

In the studied case, the identification results of damping ratio remain rather stable, i.e., the MPV value does not change significantly, when analysis window lengths around 200 s or more are used. Similar behavior is observed also for the identification results of modal excitation. The identification results of natural frequency are precise enough for practical purposes even if the length of the analysis window is very short.

B. Modal Identification Results for the Nordic Power System Simulation Model

Fig. 9 shows an example power spectrum of the ambient data described in Section IV B. Similarly to Fig. 7, the figure also shows the frequency band used for modal identification.

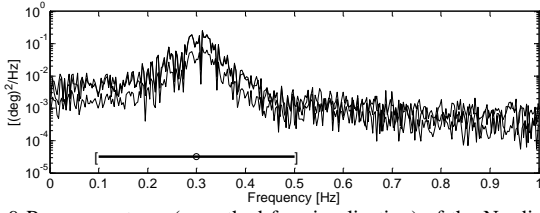


Fig. 9 Power spectrum (smoothed for visualization) of the Nordic simulation model data. Horizontal bar indicates selected frequency band for modal identification.

Figs. 10–12 show the modal identification results with different analysis window lengths and signal-to-noise ratios (SNR).

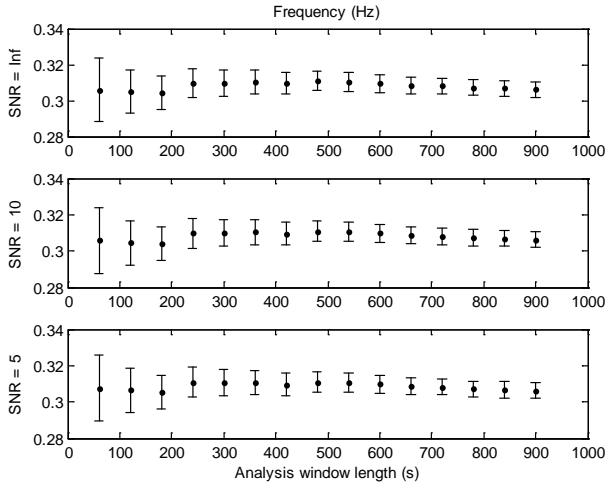


Fig. 10 Identified natural frequency for the Nordic simulation model data for different analysis window lengths and different signal-to-noise ratio (SNR). Dot: MPV; error bar: \pm two standard deviations. The reference value (Section IV B) for frequency of the studied mode is approximately 0.3 Hz.

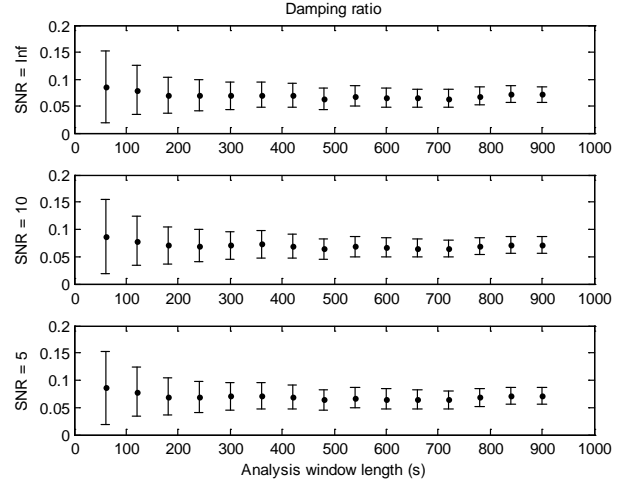


Fig. 11 Identified damping ratio for the Nordic simulation model data for different analysis window lengths and different signal-to-noise ratio (SNR). Dot: MPV; error bar: \pm two standard deviations. The reference value (Section IV B) for damping ratio of the studied mode is approximately 0.07.

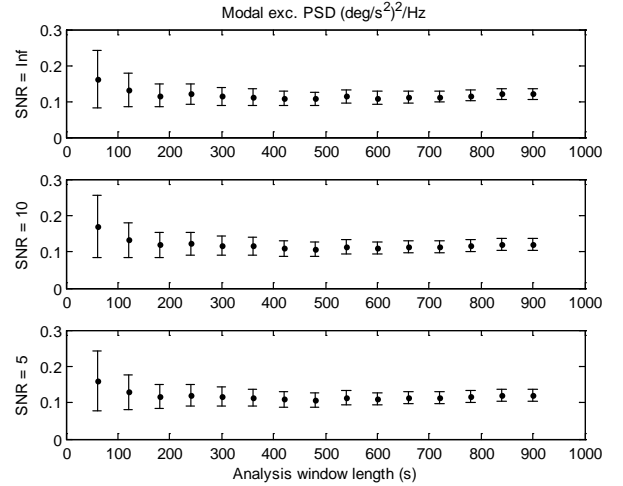


Fig. 12 Identified modal excitation PSD for the Nordic simulation model data for different analysis window lengths and different signal-to-noise ratio (SNR). Modal excitation PSD in $(\text{deg/s}^2)^2/\text{Hz}$. Dot: MPV; error bar: \pm two standard deviations.

The results in Figs. 10–12 show that the Bayesian method works similarly for the Nordic power system simulation model as for the New England test system. As the analysis window length increases the posterior PDFs are more focused towards the reference values (Section IV B) of the modal parameters.

Again, when the analysis window length is sufficient, the identification uncertainty is small. As far as modal identification with the Bayesian method is concerned, the SNRs are typically high enough and asymptotically they do not affect the identification precision [5]. The level of identification uncertainty shown in the plots stems primarily from the unknown nature of the input excitation.

C. Modal Identification Results for the Measurements Collected from Nordic Power System

Fig. 13 shows the modal identification results for a 24-hour data set collected from the Nordic power system using the Bayesian method. Modal identification is performed at a 1 minute interval, each time using a 5-minute moving analysis

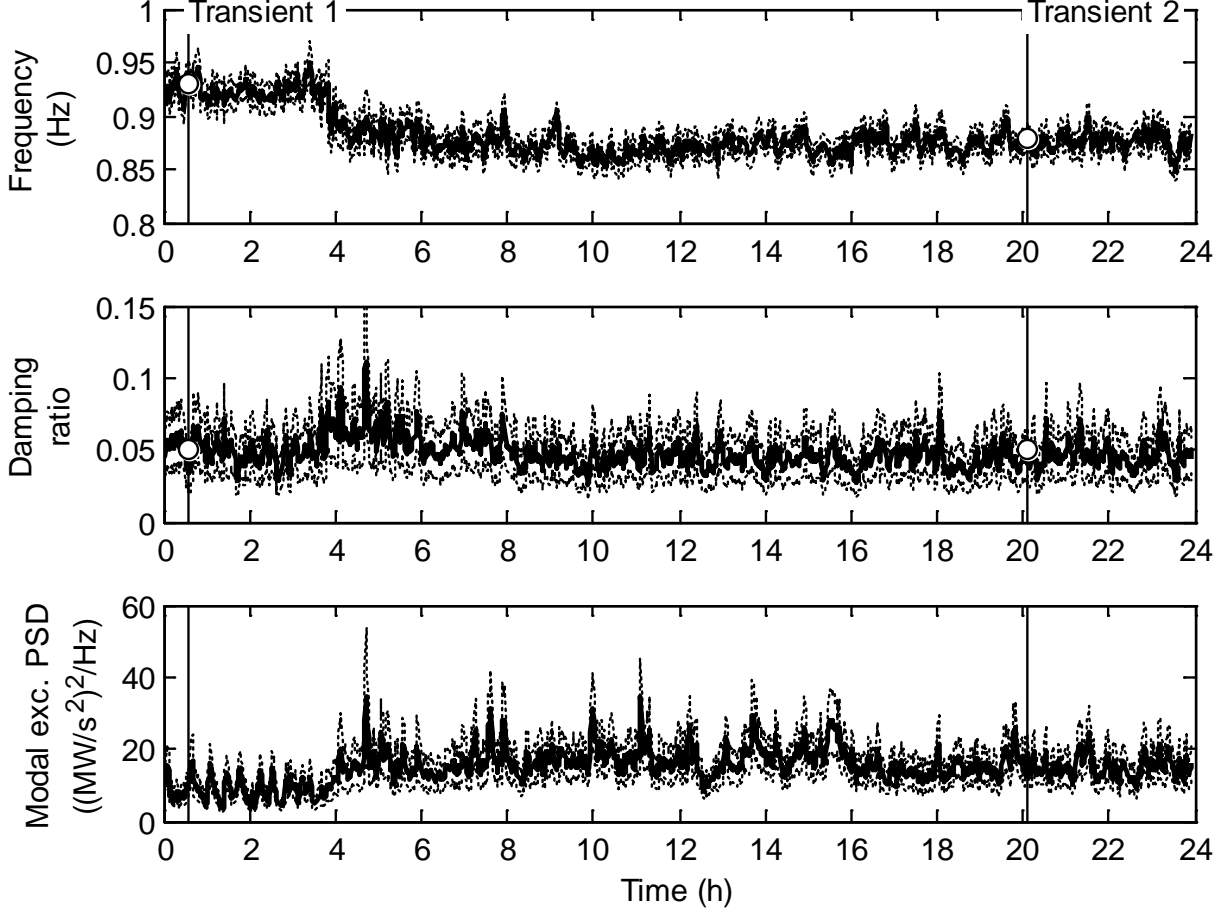


Fig. 13. Results of the Bayesian analysis for the measurement data collected from the Nordic power system. The thick line in each figure shows the MPV and the dots below and above it show the \pm two posterior standard deviation bounds. The white circles show the results of the Prony analysis of the transients (i.e., reference values for frequency and damping, Section IV C).

window. The focus of the identification is on the 0.8 Hz mode observed in Northern Finland and Northern Norway.

The results of the Bayesian analysis (Fig. 13) indicate that the frequency of the dominant mode remains rather constant during the analyzed period. The damping ratio and the PSD of the modal excitation, however, have slightly higher variations. This is rather typical for the transmission system in Northern Finland. In addition, the results in Fig. 13 show that the modal identification results are consistent with the results of the Prony analysis of the transients (presented in Section IV C). This indicates that the Bayesian method is functional for analyzing the measurement data collected from the Nordic power system.

VI. DISCUSSION

The results presented in Section V clearly show that the proposed Bayesian approach is a functional method for identifying the modal characteristics (such as damping ratios, frequencies, and modal excitation) of electromechanical oscillatory modes. The modal characteristics of the dominant electromechanical mode in the IEEE New England test system were identified with good accuracy using the Bayesian

approach. In addition, the 0.3 Hz inter-area oscillatory mode between Finland and Sweden was identified reliably using simulated measurements from the detailed Nordic power system simulation model. Furthermore, the proposed Bayesian approach was shown to be functional in identifying the modal properties of the 0.8 Hz mode observed in the Northern Finland and Norway systems from ambient PMU measurements.

The proposed Bayesian method also yields the identification uncertainty of the modal parameters. This is useful especially in real-time analyses. Consequently, power system operators or analysts may use the uncertainty information when interpreting the modal identification results. It can be also utilized in the calibration of the method (e.g., when selecting an appropriate analysis window length) or when designing measurement configurations for monitoring of certain modes.

As shown by the results in Section V B, measurement noise ($\text{SNR} = 5$ and $\text{SNR} = 10$) had virtually no influence on the accuracy of the modal identification results given by the Bayesian approach. Since the SNR of actual PMU measurements is typically reasonably high (between 30 and 5) [10], measurement noise can be expected to be insignificant in

terms of accuracy of the modal identification results given by the method.

The selection of the analysis window length has more significant effect on the modal identification results than a practical level of measurement noise. Section V A and B showed that an analysis window length around 5 minutes or more was required to obtain modal identification results from the simulated data with small identification uncertainty. The same is also true for the measured data in Section V C. This is consistent with the uncertainty laws in Section III D. Thus, the identification results are consistent with the amount of data given and identification uncertainty can be properly assessed.

The length of the analysis window in real-time monitoring of modal properties is a trade-off between identification precision (the longer the better) and modeling error risk (the shorter the better) regarding time invariance of modal properties. The former depends on the natural frequency and damping ratio of the mode under question. The required analysis window for a specific precision (in relative terms) is longer for lower frequency modes and lower damping ratio. Clearly, in analysis windows where sharp changes take place there will be significant modeling error in results. However, as long as window is not too long, the sharp change can be detected from the evolution of results over different segments, as shown in Fig. 13. Currently, modal properties are typically assumed to be invariant in ambient modal identification methods. Accounting for time varying properties in identification could be one future research direction of value of real time monitoring.

It should be also noted that the proposed Bayesian method assumes a constant PSD matrix of the modal excitation in the selected frequency band. This assumption is not valid over large timescales, for example over a day-night cycle. However, in real-time modal identification, the analysis window lengths are typically from a few minutes to 20 minutes, and in such timescales, this assumption can be considered justified.

The required calculation time of the proposed Bayesian method is short. In all the studied cases, the most probable values and posterior covariance matrix of the modal properties for a given set of data were calculated typically within 0.2 seconds. The computations were performed on a Lenovo X240 (i7-4600U, 8GB RAM). The Bayesian method is clearly fast enough for real-time monitoring of power systems.

In future research, it is important to compare the performance of the Bayesian method with other previously published modal analysis methods, such as [6]–[17]. In a thorough comparison, several methods would be tested using carefully designed data sets of synthetic and real PMU data, and their performance would be analyzed over a long period of measurements in different operating conditions of the studied power system. However, acceptable means for comparing Bayesian and non-Bayesian methods have yet to be established, without which it is difficult to make a fair comparison. This is especially relevant for ambient modal identification because identification error in the absence of loading information is significant. For example, a method

should not be preferred simply because its most probable values (or best estimates in non-Bayesian context) are close to the "true value" (if exists) in a particular data set. The issue is a deeper one related to consistency between most probable value and calculated identification precision (if it can be calculated by the method). Nevertheless, carrying out a performance analysis for any method is of high importance before taking them to real-time use in actual power system control centers. Consequently, a thorough performance analysis should also be carried out for the Bayesian method before taking it to real-time use.

VII. CONCLUSIONS

This paper proposed a new Bayesian method for the measurement based analysis of electromechanical modes. The proposed method utilizes ambient PMU measurements to identify the modal parameters, such as frequencies, damping ratios and modal excitation, of the electromechanical modes. The method also yields information regarding the uncertainty of the modal parameters.

The performance of the proposed method was evaluated using simulated measurements from the IEEE New England test system. In addition, the method was applied to analyze simulated measurements obtained from the detailed Nordic power system simulation model. The method was also applied to actual measurement data received from the 220 kV transmission system of Northern Finland.

The results indicate that the proposed Bayesian approach is able to reliably identify the modal characteristics of the electromechanical modes from the simulated measurements as well as ambient PMU measurements collected from the Nordic power system. A realistic level of noise in the measurements did not disturb the modal identification results significantly. A rather short analysis window (i.e., a few minutes) was sufficient for obtaining reliable identification results.

The results also showed that the identification uncertainty calculated by the proposed method provides useful information for the interpretation and use of modal identification results. This is of high importance in real-time analyses. The uncertainty information may also help in the calibration of the method (i.e., selection of a required analysis window length).

The Bayesian approach is a promising identification method for the measurement based modal analysis of power systems. In the future, the Bayesian approach may be used to support the work of power system operators and power system analysts in both real-time and offline analyses.

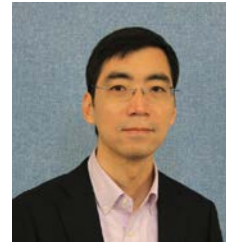
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